Stablecoin Shocks

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Abstract

We develop novel measures of stablecoin shocks and use them to identify the causal effects of stablecoin adoption on U.S. financial markets. Combining a daily narrative dataset of stablecoin-specific news with changes in the combined market capitalization of USDC and USDT, we measure high-frequency movements in stablecoin market capitalization and implement heteroskedasticity-based identification within an event-study and SVAR-IV framework. Stablecoin demand shocks have triggered persistent declines in short-term Treasury yields, a depreciation of the U.S. dollar, and gradual spillovers into crypto and equity markets. We also document heterogeneous effects across firms: payment providers benefit from greater stablecoin adoption, whereas banks—including community and small banks—show no evidence of priced disintermediation risk. Our findings highlight stablecoin demand as a novel channel of asset-market transmission.

Keywords: Stablecoin, Payment Systems, Crypto, Financial Markets
JEL Codes: E42, G12, G15

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1 Introduction

Stablecoins have rapidly evolved into one of the fastest-growing segments of the crypto financial ecosystem. Originally designed as a settlement instrument to facilitate trading on crypto exchanges, stablecoins have increasingly migrated towards broader uses, including cross-border payments and tokenized financial services. Their combined market capitalization—dominated by Tether (USDT) and USD Coin (USDC)—has grown from less than US$5 billion in 2019 to more than US$300 billion by October 2025. On the regulatory front, multiple jurisdictions have introduced dedicated frameworks to govern these instruments, including the European Union's Markets in Crypto-Assets (MiCA) regulation, which came into effect in December 2024, and the Guiding and Establishing National Innovation for U.S. Stablecoins (GENIUS) Act, enacted in the United States in July 2025.

Despite their growing global footprint, systematic evidence on the causal effects of stablecoin adoption on financial markets remains scarce. Existing empirical work has focused primarily on their association with U.S. Treasury yields, relying on instruments derived from crypto-asset price movements (Ahmed and Aldasoro, 2025). This paper fills this gap by constructing high-frequency changes in stablecoin market capitalization, which we then use to characterize shocks to stablecoin adoption—what we refer to as stablecoin shocks. We then examine their causal effects on key financial variables including U.S. Treasury markets, the value of the U.S. dollar, and the equity valuations of firms and financial institutions that may be exposed to rising stablecoin adoption.

We propose a novel narrative approach for identifying stablecoin shocks. We begin by constructing a dataset of daily stablecoin-related news events from 2019 onward using Google News, isolating episodes that originate within the stablecoin ecosystem but are not triggered by broader macro-financial developments. We then measure the high-frequency changes in the combined market capitalization of USDC and USDT on these event days. Because stablecoin supply adjusts to meet demand and maintain the peg, we cannot rely on price movements—as is common in the high frequency identification literature and in recent work identifying crypto shocks based on changes in Bitcoin prices (Cesa-Bianchi and Pinchetti, 2025). Instead, variations in stablecoin market capitalization predominantly reflect net issuance and redemption, allowing our measure to be interpreted as shocks to demand for stablecoins.

Next, we implement a heteroskedasticity-based identification strategy following Rigobon (2003) and Rigobon and Sack (2004) within both event-study and structural vector autoregression (SVAR) frameworks. This approach enables us to estimate the effects of stablecoin shocks under minimal econometric assumptions. In particular, identification does not rely on standard short-run zero restrictions or on assuming that no other disturbances affect stablecoin demand within the one-day window. Rather, the key identifying assumption is

that the variance of stablecoin shocks is larger on event days than on non-event days.

Our results reveal three main findings. First, the event-study estimates show that stablecoin shocks exert statistically significant downward pressure on short-term U.S. Treasury yields (1-month and 3-month), consistent with the reserve composition of major stablecoin issuers and the implied increase in demand for U.S. Treasury bills. The effects attenuate at longer maturities (1-year and 10-year), suggesting limited impact on the broader yield curve. The dynamic results from the SVAR-IV estimates indicate that these effects are persistent and strengthen over time. A stablecoin shock corresponding to a 1 percent increase in the combined USDC and USDT market capitalization, lowers the 1-month T-bill yield by approximately 1.9 basis points, with the trough reached around week 24.

Second, we document spillovers to broader financial markets that materialize over time. The broad dollar index depreciates modestly, by approximately 0.09 percent at its trough, consistent with lower short-term U.S. yields prompting global portfolio rebalancing. This negative effect implies that rebalancing forces dominate potential appreciation pressures from foreign demand for U.S. stablecoins which appears to remain limited relative to the size of global cross-border payments (Cerutti et al., 2025). The Bloomberg Galaxy Crypto Index (BGCI) increases by roughly 1.5 percent at its peak, indicating that increases in stablecoin demand generate spillovers into broader crypto asset markets. Equity prices exhibit a more muted reaction: the S&P 500 increases by about 0.25 percent.

Third, in the event-study setup, we show that stablecoin shocks generate heterogeneous equity responses across market segments. Payment providers—especially firms that have built stablecoin-based infrastructure—experience positive returns in response to increases in the stablecoin market capitalization. In contrast, banks, including community and small banks which are frequently highlighted as the segments most exposed to potential deposit outflows, as well as major retailers, do not show significant reactions. This suggests that markets do not currently price substantial risk of disintermediation or stablecoin-based competition.

Our results are robust across a wide range of sensitivity analyses. One caveat of the narrative approach is that the selection of events involves judgment regarding which news satisfy the criteria for inclusion in the event sample, given that no database systematically tracks major USDC- and USDT-related developments. Although we restrict attention to major events that originate within the stablecoin ecosystem and demonstrate robustness to alternative event day selections, we further complement our narrative-based strategy with a max-share approach following Uhlig (2004). The max-share method recovers stablecoin shocks as the structural disturbances that maximize the forecast error variance of the stablecoin market capitalization within the VAR. This strategy does not rely on narrative judgment and is well suited for tracing the persistent effects of stablecoin shocks. We find close align-

ment of the results across the two complementary identification strategies, underscoring the robustness of our findings.

Additionally, we show that our results are not driven by the specific set of narrative events: the results are unchanged when (i) excluding events that coincide with major macroeconomic announcements or FOMC decisions, (ii) restricting the sample to regulatory events, and (iii) using an alternative set of twenty events with the largest changes in market capitalization.

Finally, the findings are stable across alternative VAR specifications. Varying the lag order leaves the results qualitatively unchanged. The results are also robust to replacing 1-month Treasury yields with 3-month Treaury yields and to replacing the BGCI with the Bitcoin price.

Related literature. Our paper contributes to the nascent literature assessing the implications of the rise of stablecoins on financial markets. We contribute to the emerging empirical literature that examines the financial market consequences of increasing stablecoin adoption. Although the theoretical literature on stablecoins has expanded rapidly, empirical evidence remains scarce. Barbon et al. (2023) study how U.S. monetary policy affects stablecoin lending rates and find that stablecoin lending markets are primarily driven by crypto-specific demand-driven shocks. Auer et al. (2025) examine the drivers of cross-border stablecoin flows. A recent attempt at causal identification by Ahmed and Aldasoro (2025) relates stablecoin market capitalization to U.S. Treasury yields using instruments derived from crypto shocks in Aldasoro et al. (2025). Kim (2025a) analyze large Tether issuance events using high-frequency data from the Ethereum blockchain and document a significant increase short-term Treasury prices. Other papers examine narrower segments of the market: focusing on the period between January 2020 and November 2021 and measuring two-day changes in the stablecoin market capitalization, Kim (2025b) shows that an increase in the number of stablecoins in circulation raises commercial paper issuance quantity and lowers commercial paper yields the following day, while Barthélemy et al. (2025) find that positive demand shocks from stablecoin issuers increase commercial paper issuance without affecting rates. Overall, existing analyses either rely on shocks derived as residuals from regressing a crypto price index on macro-financial variables (Ahmed and Aldasoro, 2025) or focus on specific issuers or market segments.

In contrast, our paper is the first to identify stablecoin shocks using both narrative identification and the complementary max-share approach to examine its effects on financial markets within a unified empirical framework. Deploying these two approaches allows us to construct weekly series of stablecoin shocks and to study their causal effects on key macro-financial variables including Treasury yields, the value of the U.S. dollar, and equity prices. Given the rapid growth of the stablecoin market and its increasing integration with tradi-

tional financial intermediaries, our shock series provide a novel empirical tool for assessing the financial stability implications of stablecoin adoption and offers a foundation for future work examining causal links between stablecoins and macro-financial outcomes.

We also contribute to the literature on shock identification by extending the use of narrative identification and the max-share approach to the stablecoin setting. The narrative identification uses heteroskedasticity-based identification, which has been widely applied in the literature ranging from monetary policy shocks (Rigobon and Sack, 2004; Wright, 2012) to trade policy shocks (Boer et al., 2023). The max-share approach, originally proposed by Barsky and Sims (2011), has been used to identify news shocks about future technology and serves here as a robustness strategy that does not depend on narrative event selection. These two approaches allow us to recover exogenous stablecoin shocks, which are suitable for tracing the causal transmission of stablecoin adoption to financial markets and the macroeconomy.

The remainder of the paper is structured as follows. Section 2 describes the data and discusses the identification strategy and empirical methodology. Section 3 presents the findings. Section 4 concludes.

2 Data and Identification

Our empirical strategy relies primarily on heteroskedasticity-based identification, exploiting narrative-based stablecoin events in an event-study and VAR setting. We also use a max-share approach in a VAR as a complementary robustness strategy to verify the dynamic effects of stablecoin shocks.

2.1 Data

We construct a high-frequency dataset that consists of stablecoin market capitalization, asset prices, and broader financial market indicators. Stablecoin events are identified from Google News and associated effects are measured using changes in the combined market capitalization of USDC and USDT obtained from CoinGecko. Financial market data are drawn from standard sources. The US Treasury yields, the Nasdaq-100 index, the Bloomberg Galaxy Crypto Index—a benchmark for major cryptocurrencies—and the equity prices of major payment providers, retailers, and banking institutions are obtained from Bloomberg. The S&P 500 index, and the broad dollar index are collected from FRED.

The sample spans January 1, 2019 to June 30, 2025. We use daily observations for the event-study analysis and aggregate them to the weekly frequency for the VAR estimations. A detailed overview of the data and sources can be found in Table A.1 in Appendix A.

2.2 Narrative Identification

The narrative identification isolates exogenous variation in stablecoin demand based on a set of news events. We select events that reflect regulatory, technological, or sentiment-related developments specific to the stablecoin ecosystem. We then construct a series of daily changes in the stablecoin market capitalization on the event days, and use heteroskedasticity-based identification to estimate causal contemporaneous and dynamic responses of U.S. Treasury yields and other key financial market indicators to stablecoin shocks.[1]

High-frequency series. To construct the series of high-frequency changes in the stablecoin market capitalization induced by stablecoin-related events, we first identify a set of exogenous events that affect stablecoin demand but are unrelated to any macroeconomic or financial developments as well as to broader crypto asset developments. To do so, we conduct a systematic week-by-week search of Google News beginning in January 2019, using a set of keywords including 'stablecoin', 'stablecoins', 'USD Coin', 'USDC', 'Tether', and 'USDT'. We review each news item manually and apply narrative judgment to retain only those events that originate within the stablecoin ecosystem and are not driven by developments in the broader crypto or macro-financial environment.

Following this procedure, we identify 50 distinct events, as summarized in Table A.2 in Appendix A. Examples of retained events include: the introduction of the GENIUS stablecoin bill by U.S. Senator Hagerty (February 4, 2025); the strategic partnership announcement between Circle and Binance (December 11, 2024); and remarks by Fed Chair Powell emphasizing the central bank's role in overseeing stablecoins (June 21, 2024). In contrast, we exclude events that originate outside the stablecoin ecosystem—such as broader banking or crypto-sector disruptions—even if they significantly impact stablecoin market capitalization. Examples include the failure of Silicon Valley Bank (March 10, 2023) and the bankruptcy filing of crypto exchange FTX (November 11, 2022).[2]

To measure the market response to the identified events, we use daily market capitalization data. For each event date, we measure the change in the combined market capitalization of USDC and USDT on the given day:

$$\Delta m_t = m_t - m_{t-1}, \tag{1}$$

[1] Throughout the paper, 'stablecoin market capitalization' refers to the combined market capitalization of USDC and USDT.

[2] We also exclude the following events: (i) events on days with a positive change in the USDT market capitalization and a negative change in the USDC market capitalization, and vice versa and (ii) events which originate in non-USDT or non-USDC stablecoins and do not have implications for the broader stablecoin ecosystem.

where m_t is the log of the market capitalization at the end of day t. Since crypto markets are open 24/7, the daily data gives us a 24-hour window for the high-frequency changes. We assess that a 24-hour window is adequate to capture the market response to the identified events, which given the nature of the events and market structure may take longer to transmit than other macro-financial events, such as monetary policy surprises. It also enables us to capture the demand responses to our identified events, even when the exact timing of the events are not known. Because stablecoin prices are designed to remain fixed and exhibit only minimal transitory deviations, fluctuations in market capitalization arise almost entirely from net issuance or redemption. Consequently, changes in market capitalization provide a direct measure of changes in stablecoin demand.

Because daily changes in the stablecoin market capitalization provide an imperfect proxy for the demand response to the identified events, we use these changes as instruments for shocks to stablecoin demand rather than as direct measures of the underlying shock. Our identification does not require that daily market capitalization changes fully capture each event's response; it requires only that (i) the events induce some within-day adjustment in the stablecoin market capitalization, and (ii) the instruments we construct using the daily changes capture a sufficient amount of the movements in the stablecoin market capitalization that is induced by the stablecoin shock. High-frequency identification approaches commonly rely on rapid price adjustments in financial assets in response to news. Stablecoins, in contrast, maintain their peg to the underlying asset. Nonetheless, market-capitalization changes are significantly larger on event days than on non-event days, indicating within-day responses to the identified events. First-stage diagnostics further confirm that the instrument is sufficiently strong, capturing meaningful unexplained variation in stablecoin market capitalization in the VAR. We discuss this in more detail in Section 3.2.

For each event date, we randomly select a control date, which allows us to perform a placebo test to compare market responses on event dates relative to control dates. To select appropriate control dates for each event, we randomly select a date that is less than two months away from the event date, but at least three days away from any event date. This ensures that the control dates are comparable to the event dates, while also being sufficiently far away to not capture effects from the identified events. We find that the changes in market capitalization on event dates are significantly larger in magnitude relative to the control dates. The average absolute change in market capitalization on event dates is 0.42 percent, compared with 0.25 percent on control dates. The variance of the series of market responses on event dates is 2.18 times that of the control series. Using the Brown-Forsythe test of group variances, we confirm that the difference in variance is statistically significant with a p-value of less than 0.05.

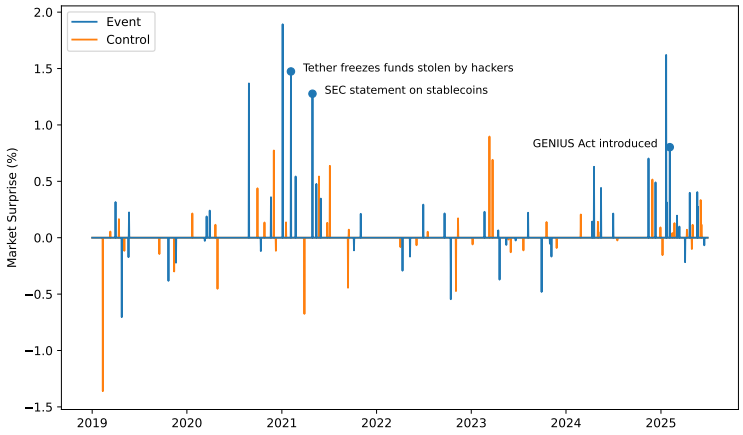


Figure 1: Stablecoin market capitalization movement series around event and control days

Notes: This figure shows the daily stablecoin market changes around selected event days and corresponding control days as outlined in section 2.2 and Equation 1.

Event-study analysis. To estimate the high-frequency responses of key financial variables to stablecoin shocks, we use the heteroskedasticity-based identification strategy following Rigobon (2003) and Rigobon and Sack (2004).

The identification is motivated by the following simultaneous equation model:

$$\Delta m_t = \beta \Delta y_t + \gamma F_t + \nu_t, \tag{2}$$

$$\Delta y_t = \alpha \Delta m_t + F_t + \eta_t, \tag{3}$$

where Δm_t is the change in the stablecoin market capitalization within an event window at time t; Δy_t is the change in the outcome variable of interest (e.g. U.S. Treasury yields, stock market index, etc.) within an event window at time t; F_t is a single unobserved factor that moves both the stablecoin market capitalization and the outcome of interest (normalized to correspond one-to-one with Δy_t); ν_t is a stablecoin shock; and η_t is a shock to the outcome variable. The shocks are neither serially correlated nor correlated with each other. Our coefficient of interest is α, which measures the causal effect of a change in the stablecoin market capitalization on the outcome variable of interest.

An event-study framework that estimates a simple OLS of regressing Δy_t on Δm_t assumes that all changes to the stablecoin market capitalization during the event windows are driven exclusively by idiosyncratic shocks to the stablecoin market capitalization ν_t. This implicitly assumes that there is no background noise, meaning that both F_t and η_t are precisely 0 during all event windows. The heteroskedasticity-based identification relaxes these assumptions. We allow for the presence of both the common factor F_t and the idiosyncratic shock to the

outcome variable η_t during the event windows. The key identifying assumption we impose is that the variance of the idiosyncratic shock to the stablecoin market capitalization, ν_t, is higher on event days than non-event days, while the variances of other factors (F_t and η_t) are the same on event days and non-event days.

Formally, the identifying assumption is the following:

$$\sigma^2_{\nu,S} > \sigma^2_{\nu,\tilde{S}}, \tag{4}$$

$$\sigma^2_{F,S} = \sigma^2_{F,\tilde{S}}, \tag{5}$$

$$\sigma^2_{\eta,S} = \sigma^2_{\eta,\tilde{S}}, \tag{6}$$

where $\sigma^2_{i,j}$ represents the variance of shock i for sample $j \in \{S, \tilde{S}\}$. The samples S and $\tilde{S}$ represent the set of event days and control days, respectively. We include all dates that are at least three days away from any event date in our set of control dates.[3]

Assuming that the simultaneous equation model in Equations 2–3 are correctly specified and Equations 4–6 hold, we can estimate the coefficient of interest, α, using the covariance matrices of Δy_t and Δm_t on event days and control days. We outline the algebraic derivations and the steps to estimate α in Appendix B.1.

SVAR-IV analysis. To estimate the dynamic causal effects of stablecoin shocks on key financial variables, we implement the SVAR-IV methodology by using the series of market capitalization changes on event days as an external instrument for stablecoin shocks.

We first estimate a reduced-form VAR in levels at the weekly frequency using relevant variables. We include the log stablecoin market capitalization, 1-month U.S. Treasury yields, log Bloomberg Galaxy Crypto Index, log S&P 500, and log broad dollar index in our baseline specification:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \mathbf{B}_1\mathbf{y}_{t-1} + \ldots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{7}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables; $\boldsymbol{\alpha}$ is an $n \times 1$ vector of constants; $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices; and $\mathbf{u}_t$ is the $n \times 1$ vector of reduced-form innovations with covariance matrix $\boldsymbol{\Sigma}$. We set the lag length p to 13 weeks (one quarter of a year).

We impose a structural assumption that there is a linear mapping between the reduced-

[3]The set of control days $\tilde{S}$ may consist of either the entire sample of non-event days or a selected sample of days that are most comparable to the event days in terms of background noise. Känzig (2021) selects control dates from the same day of the week in the months prior to each announcement; Hébert and Schreger (2017) classify all dates as control dates if they are at least two days away from any event and at least two days away from any "excluded events" that they characterize.

form innovations $\mathbf{u}_t$ and an $n \times 1$ vector of mutually uncorrelated structural shocks $\boldsymbol{\varepsilon}_t$:

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t, \tag{8}$$

where $\mathbf{S}$ is a nonsingular $n \times n$ matrix mapping the structural shocks to the reduced-form innovations. This assumes that the VAR is invertible, meaning that the VAR contains all the information required to recover the structural shocks (Stock and Watson, 2018). We denote the covariance of $\boldsymbol{\varepsilon}_t$ as Ω.

We make the assumption that one of the structural shocks is a stablecoin shock, which we denote as ε_t^d. We can denote the first element of the structural shocks, $\varepsilon_{1,t}$, to represent the stablecoin shock ε_t^d, implying that the first column of $\mathbf{S}$ captures the effect of ε_t^d on $\mathbf{u}_t$. Identifying the first column of $\mathbf{S}$, which we denote as $\mathbf{s}_1$, allows us to estimate the dynamic causal effects of the stablecoin shock ε_t^d on the variables in the VAR.

Following a similar set of assumptions to those used in the event-study analysis discussed above, we exploit heteroskedasticity in the series of market capitalization changes to estimate $\mathbf{s}_1$. We formally outline the assumptions and the derivations to estimate $\mathbf{s}_1$ in Appendix B.2. Using the estimate of the structural impact vector $\hat{\mathbf{s}}_1$ and the coefficient matrices $\hat{\mathbf{B}}_1, \ldots, \hat{\mathbf{B}}_p$ from the reduced-form VAR estimates, we can directly estimate impulse response functions and the structural shock series.

2.3 Max-Share Identification

The complementary approach recovers the stablecoin shock within a VAR using max-share identification following Uhlig (2004). We first estimate a reduced-form VAR. We then identify shocks using the max-share approach for all variables in the VAR except stablecoin market capitalization. In the final step, we identify the stablecoin shock by applying the max-share approach subject to the additional constraint that the shock is orthogonal to all other identified shocks.

Under this setup, we estimate a reduced-form VAR using the same specification as in the narrative approach at the weekly frequency:

$$\mathbf{y}_t = \boldsymbol{\alpha} + \mathbf{B}_1\mathbf{y}_{t-1} + \ldots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{9}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables consisting of log stablecoin market cap, 1-month Treasury yields, log Bloomberg Galaxy Crypto Index, log S&P 500, and log broad dollar index in our baseline specification.[4] $\boldsymbol{\alpha}$ is an $n \times 1$ vector of constants; $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices; and $\mathbf{u}_t$ is the $n \times 1$ vector of reduced-form innovations with

[4] We use 1-month Treasury yields, as they best captures the average maturity of the stablecoin reserves.

covariance matrix $\mathbf{\Sigma}$. We set the lag length p to 13 weeks.

We impose the same structural assumption as in the narrative approach that there is a linear mapping between the reduced-form innovations $\mathbf{u}_t$ and an $n \times 1$ vector of mutually uncorrelated structural shocks $\boldsymbol{\varepsilon}_t$:

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t, \tag{10}$$

where $\mathbf{S}$ is a nonsingular $n \times n$ matrix mapping the structural shocks to the reduced-form innovations. Any admissible impact matrix $\mathbf{S}$ satisfying $\mathbf{S}\mathbf{S}' = \mathbf{\Sigma}$ can be written as $\mathbf{S} = \tilde{\mathbf{S}}\mathbf{Q}$, where $\tilde{\mathbf{S}}$ is the Cholesky decomposition of $\mathbf{\Sigma}$ and $\mathbf{Q}$ is an orthonormal rotation. Therefore, identification consists of finding $\mathbf{Q}$.

To identify the stablecoin shock using the max-share approach, we will identify a series of shocks that each explains the maximum amount of the forecast-error variance for a target variable up to a specific horizon. The forecast-error for horizon h can be expressed as

$$\mathbf{y}_{t+h} - \mathbb{E}_{t-1}[\mathbf{y}_{t+h}] = \sum_{\ell=0}^{h} \mathbf{B}_\ell \tilde{\mathbf{S}}\mathbf{Q}\boldsymbol{\varepsilon}_{t+h-\ell}. \tag{11}$$

Let $\mathbf{B}_{i,\ell}$ denote row i of $\mathbf{B}_\ell$ and $\mathbf{q}_j$ denote the jth column of $\mathbf{Q}$. The share of the forecast-error variance of variable i at horizon h explained by structural shock j is

$$\mathcal{S}_{i,j}(h) \equiv \frac{\sum_{\ell=0}^{h} \mathbf{B}_{i,\ell}\tilde{\mathbf{S}}\mathbf{q}_j\mathbf{q}_j'\tilde{\mathbf{S}}'\mathbf{B}_{i,\ell}'}{\sum_{\ell=0}^{h} \mathbf{B}_{i,\ell}\mathbf{\Sigma}\mathbf{B}_{i,\ell}'}. \tag{12}$$

Let $\mathcal{J}_{-1}$ be the set of indices for all non-stablecoin variables in the VAR. For each $i \in \mathcal{J}_{-1}$, we identify the shocks by maximizing the FEV of a given variable up to a specific horizon H:

$$\mathbf{q}_i^* = \arg\max_{\mathbf{q}_i} \sum_{h=0}^{H} \mathcal{S}_{i,i}(h) \text{ s.t. } \mathbf{q}_i'\mathbf{q}_i = 1. \tag{13}$$

This follows the methodology from Barsky and Sims (2011), where we identify the shock using the cumulative share of the forecast-error variance. In the baseline specification, we set the horizon H to be 13 weeks. Note that we do not impose any interpretations of the shocks identified for the non-stablecoin variables. This step is merely an intermediate step to identify shocks that we want to purge out when identifying the stablecoin shock.

Finally, we can identify $\mathbf{q}_1$, which we denote as the column of $\mathbf{Q}$ corresponding to the stablecoin shock. We maximize the FEV of the stablecoin market capitalization up to a specific horizon H, while also imposing orthogonality with respect to the shocks corresponding

to all of the other variables in the VAR.

$$\mathbf{q}_1^* = \arg\max_{\mathbf{q}_1} \sum_{h=0}^{H} \mathcal{S}_{1,1}(h) \text{ s.t. } \mathbf{q}_1'\mathbf{q}_1 = 1 \text{ and } \mathbf{q}_1'\mathbf{q}_\mathbf{i}^* = \mathbf{0}\ \forall \mathbf{i} \in \mathcal{J}_{-\mathbf{1}}. \tag{14}$$

Once we obtain $\mathbf{q}_1^*$, the structural impact vector of the stablecoin shock can be obtained using

$$\mathbf{s}_1 = \tilde{\mathbf{S}}\mathbf{q}_1^*. \tag{15}$$

Similarly to the narrative approach, we can directly estimate impulse response functions and the structural shock series using the estimates of the the structural impact vector and the coefficient matrices from the reduced-form VAR.

3 Effects of Stablecoin Shocks on Financial Markets

In this section, we provide evidence on the causal effects of stablecoin shocks on key financial market indicators. We first study the high-frequency responses of U.S. Treasury yields and other key financial market indicators including equity prices, the broad dollar index, and the Bloomberg Galaxy Crypto Index (BGCI). Next, we explore the dynamic responses of the same set of variables.

3.1 High-Frequency Causal Effects of Stablecoin Shocks

Table 1 presents the results estimating the high-frequency responses to stablecoin shocks using the event-study methodology from Section 2.2. All outcome variables and the explanatory variables are in logs, except for U.S. Treasury yields, which are in basis points. We use one-day windows for all variables.

We find that a stablecoin shock associated with a 1 percent increase in the market capitalization leads to statistically significant decreases in the 1-month and 3-month Treasury yields of 0.423 and 0.498 basis points, respectively. In contrast, the effects on longer-term U.S. Treasury yields are smaller in magnitude: the 1-year and 10-year yields decrease by 0.328 and 0.231 basis points, respectively, though the estimates are statistically insignificant. This finding is consistent with the fact that short-term Treasury securities make up a significant share of stablecoin issuers' reserves; higher stablecoin demand therefore translates into increased demand for T-bills. As of end-October 2025, 35 percent of USDC reserves consisted of U.S. Treasury securities maturing within three months, with the remainder of reserves consisting of cash and U.S. Treasury repurchase agreements. Although USDT's

	U.S. Treasury 1M	U.S. Treasury 3M	U.S. Treasury 1Y	U.S. Treasury 10Y
	(1)	(2)	(3)	(4)
Stablecoin Market Cap	-0.423*	-0.498***	-0.328	-0.231
	(0.233)	(0.174)	(0.284)	(0.367)
Observations	1439	1439	1439	1439
	S&P 500	Nasdaq	Broad Dollar	BGCI
	(5)	(6)	(7)	(8)
Stablecoin Market Cap	0.060	0.144	-0.045**	0.239
	(0.060)	(0.092)	(0.021)	(0.382)
Observations	1437	1502	1435	1446

Table 1: High-frequency responses to stablecoin shocks: financial markets

Notes: This table reports the results for the event-study analysis using heteroskedasticity-based identification. We use one-day windows for this event-study analysis. All regressions use heteroskedasticity-robust standard errors. *p<0.1; **p<0.05; ***p<0.01.

reserves include a more diverse range of assets—including Bitcoin and commodities—62 percent of its reserves were in the form of T-bills as of its most recent reserve report in September 2025.[5] The GENIUS Act stipulates that, in the future, reserve holdings must be composed of highly liquid assets including Treasuries with a maturity of 93 days or less.

We also examine the effect of a stablecoin shock on other key financial market and crypto-related variables. Our results indicate that a stablecoin shock associated with a 1 percent increase in the market capitalization weakens the broad dollar index by 0.045 percent. Stablecoin demand can impact the strength of the U.S. dollar through two opposing channels. On the one hand, lower U.S. Treasury yields may weaken the U.S. dollar by triggering global portfolio rebalancing away from U.S. assets. On the other hand, higher demand for U.S. stablecoins from abroad could strengthen the U.S. dollar. The observed negative response of the broad dollar index suggests that the first channel dominates, a finding consistent with stablecoins' still limited footprint in the global cross-border payments market (Cerutti et al., 2025).

The response of the Bloomberg Galaxy Crypto Index (BGCI) is insignificant, indicating that our stablecoin shocks are well identified and are not capturing broader (unbacked) crypto-driven events. We also find insignificant responses of the S&P 500 and Nasdaq stock indexes. These results on the high-frequency responses provide further evidence that our

[5]Monthly USDC reserve holding disclosures from Circle are available at https://www.circle.com/transparency. Quarterly USDT reserve assurance reports from Tether are available at https://tether.to/en/transparency.

narrative identification strategy isolates exogenous stablecoin shocks, which are not driven by reverse causality or contamination from underlying macroeconomic or financial shocks.

We next examine whether the aggregate stock market response masks heterogeneity across market segments and types of firms. A common hypothesis is that, by enabling fast and inexpensive digital payments, stablecoins may generate tailwinds for payment providers, crypto-related firms, and major retailers, while potentially altering the competitive landscape for traditional financial institutions. To assess whether equity markets price this potential reallocation of activity, we analyze the equity responses of a number of payment providers, crypto exchanges, and large retailers.

Table 2 reports high-frequency equity responses for 10 firms with potential stablecoin exposure. Several large payment providers—PayPal and Square—exhibit positive and statistically significant responses to stablecoin shocks. Coinbase, a crypto exchange, also experiences positive and statistically significant effects, showing the largest sensitivity. A stablecoin shock associated with a 1 percent increase in stablecoin market capitalization raises its equity price by 1.436 percent. These firms have all built infrastructure to support stablecoin-based payment networks. We also find a significant positive response for Adyen, a Dutch payments company with a growing presence in the U.S. By contrast, the equity prices of Mastercard and Visa, as well as of major retailers such as Amazon and Walmart—both of which have indicated an interest in exploring stablecoin issuance—do not exhibit a significant response.

We then turn to financial institutions, which could in principle face disintermediation risks if stablecoin adoption diverts deposits and payment activity away from the banking system—risk often viewed as more acute for community and small banks, given their greater structural reliance on deposit funding. We find no evidence that markets price such risks. The equity response of the Nasdaq large banks index is statistically insignificant. Likewise, the Nasdaq community and small banks indexes—frequently highlighted as the segments most exposed to potential deposit outflows (Nigrinis, 2025; Tsyrennikov, 2025; Ahmed et al., 2025)—do not exhibit significant responses to stablecoin shocks (Table C.1).[6] Consistent with these findings, we also find no significant effects on the equity prices of the ten largest U.S. banks or the ten largest community banks (Table C.2).

3.2 Dynamic Causal Effects of Stablecoin Shocks

We now analyze the dynamic causal effects of a stablecoin shock on U.S. Treasury yields and various financial market indicators following the narrative identification approach outlined

[6]We use the following Nasdaq U.S. indexes: Large-Cap Banks Index, ABA Community Bank Index, and Small-Cap Banks Index.

	Coinbase (1)	PayPal (2)	Square (3)	Mastercard (4)	Visa (5)
Stablecoin Market Cap	1.436**	0.521***	0.587**	0.147	0.091
	(0.683)	(0.193)	(0.244)	(0.111)	(0.107)
Observations	970	1502	1502	1502	1502
	Amazon (6)	Walmart (7)	Adyen (8)	Kaspi (9)	Wise (10)
Stablecoin Market Cap	0.163	-0.120	0.584**	0.457	0.199
	(0.152)	(0.133)	(0.233)	(0.319)	(0.320)
Observations	1447	1447	1474	858	889

Table 2: High-frequency responses to stablecoin shocks: payment providers and retailers

Notes: This table reports the results for the event-study analysis using heteroskedasticity-based identification. We use one-day windows for this event-study analysis. All regressions use heteroskedasticity-robust standard errors. *p<0.1; **p<0.05; ***p<0.01.

in Section 2.2.[7] To perform statistical inference and interpret the results, our instrument must be sufficiently strong. To assess this, we perform a weak instrument test and obtain a first-stage heteroskedasticity-robust F-statistic of 12.78, which is above the conventional critical value of 10, as suggested in Montiel Olea et al. (2021).

Figure 2 presents the impulse responses, which are identified up to sign and scale. Therefore, we scale the shock to have a peak response of a 1 percent increase in the stablecoin market capitalization. We find that the identified stablecoin shock is fairly persistent. This persistence is plausible, as the underlying events convey information about stablecoins which is likely to induce gradual responses in stablecoin adoption.

Our results indicate that a stablecoin shock associated with a peak response of a 1 percent increase in the stablecoin market capitalization generates a statistically significant response in short-term U.S. Treasury markets. The 1-month U.S. Treasury yield decreases by 1.9 basis points at the trough of the response. Higher stablecoin demand thus results in a persistent decline in short-term U.S. Treasury yields, mirroring that of the persistent shock. This finding aligns both in sign and in magnitude with the results reported by Ahmed and Aldasoro (2025), who highlight a relationship between stablecoin market capitalization and 3-month U.S. Treasury yields, although they do not explicitly identify exogenous stablecoin shocks.

[7] Figure B.1 presents the weekly shock series from both the narrative identification and the max-share approach.

Consistent with the high-frequency results, the broad dollar index exhibits a statistically significant response, declining by 0.09 percent at the trough and providing further evidence that increased stablecoin adoption could weaken the U.S. dollar through portfolio rebalancing in response to lower U.S. T-bill yields.

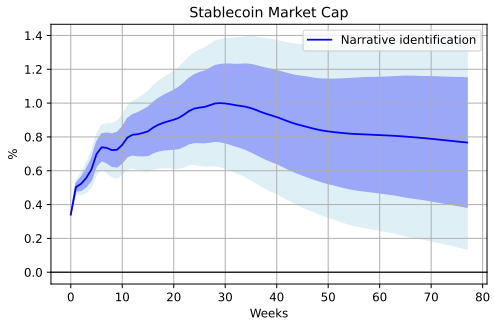
Finally, we find that the BGCI rises by 1.5 percent at its peak, suggesting that higher stablecoin demand generates spillovers into broader crypto markets . Shocks associated with an increase in stablecoin demand may facilitate easier and lower cost access to (unbacked) crypto trading (Gorton et al., 2022), thereby stimulating demand for crypto assets. We also document a positive, but small, response for the S&P 500, with a peak effect of 0.25 percent. Although the impulse response is statistically significant, its magnitude is small and economically immaterial relative to the volatility of the S&P 500. The response is around 0.1 percent in the week of impact, broadly consistent with the insignificant high-frequency event study estimates of the equity responses using S&P 500 and Nasdaq-100.

Sensitivity analyses. We perform a comprehensive set of additional tests, and find that our results are robust to a complementary identification approach, varying the specification of the VAR, number of lags, and alternative methods to select the events in our narrative identification strategy.

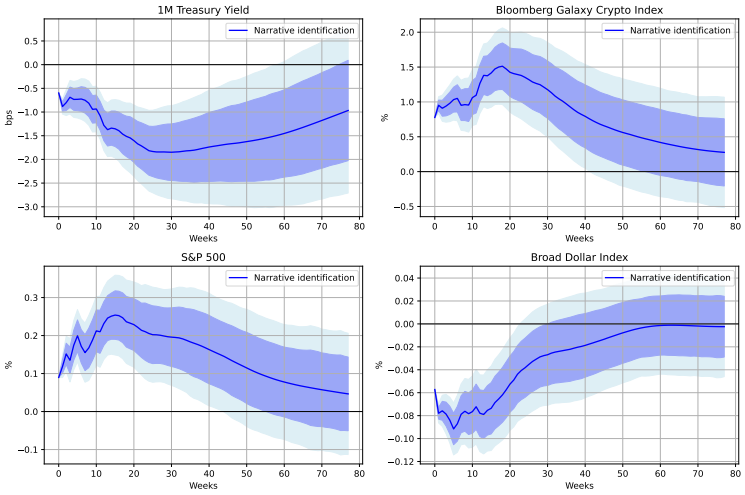
First, we show that the estimated impulse responses are robust to relying on the max-share approach instead of narrative identification. The max-share method recovers stablecoin shocks as the structural disturbances that maximize the forecast error variance of stablecoin market capitalization within the VAR and, importantly, does not rely on judgment regarding event selection. The resulting impulse responses closely mirror those obtained under the narrative identification in sign, shape, and magnitude across all variables, reinforcing the robustness of our findings (Figure 3).

Second, our results are robust to alternative methods to select the events for the narrative identification strategy as shown in Appendix D.1. To avoid potential confounding effects from overlapping information releases, we exclude events that coincide with major macroeconomic announcements or FOMC decisions and find that the results remain unchanged. All variables exhibit extremely similar responses. Restricting the sample to regulatory announcements about stablecoins likewise yields impulse responses that are nearly identical, indicating that regulatory events generate effects similar to those in the full event set. Our results are also robust to limiting our analysis to twenty events with the largest absolute change in market capitalization.

Third, in Appendix D.2, we show that the impulse responses are consistent with our baseline results when we modify the VAR specification, including augmenting the VAR with the gold price or VIX as an additional variable. We find that the responses are very similar



(a) Stablecoin market cap



(b) Other outcome variables

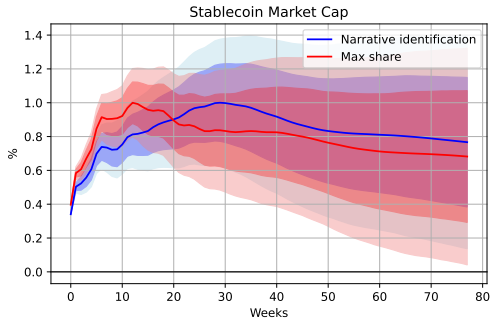
Figure 2: Impulse responses to a stablecoin shock: narrative identification

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.

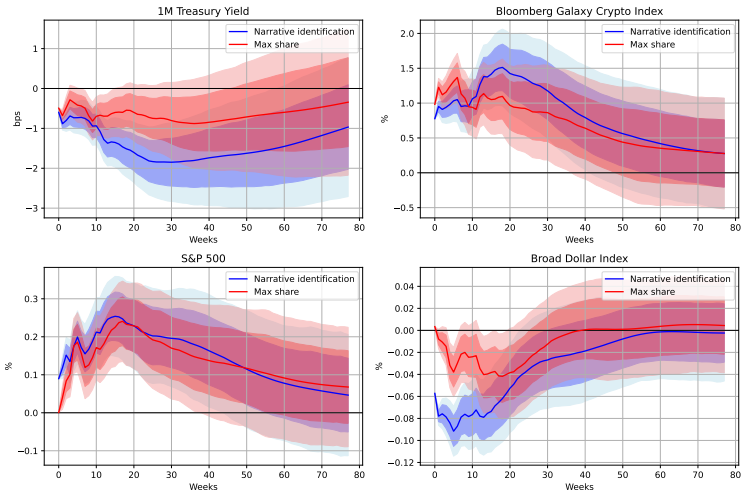
in sign, shape, and magnitude for all variables. We also find that the results are robust to replacing the 1-month Treasury yield with 3-month Treasury yields, the Bloomberg Galaxy Crypto Index with the Bitcoin price, and the S&P 500 index with the Nasdaq-100 index.

Finally, we find that our results are robust to varying the number of lags, as well as the horizon length used for the max-share approach. Appendix D.3 shows the estimated impulse responses using half a year of lags (i.e., 26 weeks), as opposed to the baseline specification of using lags corresponding to a quarter of a year (i.e., 13 weeks). Overall, the responses are more volatile for all variables due to the high number of lags. The responses for the Treasury yields are very similar, if not larger in magnitude for both identification approaches. In contrast, we find that the responses for the BGCI, S&P 500, and the broad dollar index

are more dampened for the max-share approach. Nonetheless, the overall responses are similar in sign and magnitude throughout the 1.5-year horizon of the impulse responses. Appendix D.4 shows the estimated impulse responses using a 26-week horizon for the max-share approach. This results in a more volatile shape of the response in the stablecoin market capitalization, which consequently makes interpreting the responses in other variables more difficult. The responses are still largely consistent with the baseline estimates, with the overall effect throughout the 1.5-year horizon being consistent in sign for all variables.



(a) Stablecoin market cap



(b) Other outcome variables

Figure 3: Impulse responses to a stablecoin shock: max-share identification

Notes: This figure shows the impulse responses to a stablecoin shock using two complementary identification approaches: heteroskedasticity-based identification in a SVAR-IV and the max-share approach. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.

4 Conclusion

This paper develops a novel approach for identifying shocks to stablecoin adoption and examines their effects on key segments of U.S. financial markets. By constructing a daily narrative dataset of stablecoin-specific news and quantifying high-frequency changes in stablecoin market capitalization, we provide an exogenous source of variation that can be used to study the financial implications of stablecoin adoption. Using both narrative identification within an SVAR framework and a complementary max-share approach as a robustness check, we recover stablecoin demand shocks and trace their causal impact on U.S. Treasury markets, the exchange rate, and equity valuations across a broad set of firms.

Our results yield three main conclusions. First, stablecoin demand shocks exert downward pressure on short-maturity Treasury yields, consistent with the reserve composition of major stablecoins and the associated increase in T-bill demand. Our results indicate that a stablecoin shock associated with a peak response of a 1 percent increase in the stablecoin market capitalization generates a statistically significant response in short-term U.S. Treasury markets. The 1-month U.S. Treasury yield decreases by 1.9 basis points at the trough of the response. The effects are concentrated at the short end of the curve, suggesting limited broader yield-curve implications.

Second, stablecoin shocks also generate spillovers beyond Treasury markets. We find gradual but measurable effects on broader asset prices—including crypto and equity valuations and a modest depreciation of the U.S. dollar—consistent with portfolio rebalancing in response to lower short-term yields.

Third, stablecoin shocks generate heterogeneous equity responses across market segments. Payment providers with established stablecoin-based infrastructure experience positive and statistically significant equity gains, whereas large banks, community banks, and major retailers show no meaningful responses. These findings suggest that stablecoin adoption is not currently priced as a material competitive threat to traditional financial institutions.

Our results highlight the relevance of stablecoin demand as an emerging channel of financial transmission. In light of recent regulations —including the GENIUS Act in the United States and MiCA in Europe—policies affecting stablecoin issuance may have nontrivial consequences for Treasury markets, exchange rates, and broader asset prices. As the use of stablecoins in payments and tokenized financial services expands, monitoring their interactions with traditional financial markets will be important for evaluating potential financial stability implications.

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A Data

A.1 Data Sources

Variable	Description	Source	Sample	Transf.
Stablecoin market cap	USDT + USDC market capitalization	CoinGecko	Jan 1, 2019–Jun 30, 2025	Log
U.S. Treasury yields	1m, 3m, 6m, 1y, 2y, and 10y Treasury yields	Bloomberg	Jan 1, 2019–Jun 30, 2025	Bps
Bloomberg Galaxy Crypto Index	Benchmark index of major crypto assets traded in USD	Bloomberg	Jan 1, 2019–Jun 30, 2025	Log
S&P 500	Broad U.S. equity index of about 500 large public companies	FRED	Jan 1, 2019–Jun 30, 2025	Log
Nasdaq-100	Tracks the 100 largest publicly traded non-financial firms listed on Nasdaq	Bloomberg	Jan 1, 2019–Jun 30, 2025	Log
Nominal Broad Dollar Index	Trade-weighted value of the U.S. dollar vs. major trading partners	FRED	Jan 1, 2019–Jun 30, 2025	Log
VIX	30-day expected volatility of the U.S. stock market	FRED	Jan 1, 2019–Jun 30, 2025	Log
Gold price	Daily spot price of gold in USD per troy ounce	FRED	Jan 1, 2019–Jun 30, 2025	Log
Bitcoin price	Daily USD price of Bitcoin	Chainalysis	Jan 1, 2019–Jun 30, 2025	Log
Firm and bank equity prices	Daily equity price indexes for firms and banks	Bloomberg	Jan 1, 2019–Jun 30, 2025	Log

Table A.1: Data description and sources

A.2 Stablecoin News Events

Date	Description of Event	Market Cap Change (%)
4/1/2019	Launch of TrueGBP (British stablecoin)	0.317
4/25/2019	Bitfinex covers $850M loss with Tether funds	-0.704
5/21/2019	Tether reveals that its reserves include Bitcoin and other assets	-0.173
5/23/2019	Coinbase Commerce Enables USD Coin Payments - Coinspeaker	0.224
10/22/2019	US Lawmaker Introduces Bill Classifying Stablecoins as Securities	-0.383
11/20/2019	U.S. lawmakers introduce H.R. 5197 "Managed Stablecoins Are Securities Act"	-0.222
3/10/2020	Circle announces launch of APIs for businesses to adopt USDC	-0.028
3/17/2020	MakerDAO adds USDC as DeFi collateral	0.189
3/29/2020	Visa becomes first major payments network to settle transactions in USDC	0.241
8/27/2020	USDC upgrade allows for 'gasless sends'	1.368
10/12/2020	Financial Stability Board releases regulatory recommendations for stablecoins	-0.119
11/20/2020	US government enlists USDC for 'global foreign policy objective' in Venezuela	0.360
1/4/2021	US federal regulator says banks can conduct payments using stablecoins	1.893
2/5/2021	Tether freezes $1.7 Million in response to hack	1.474
2/23/2021	Bitfinex, Tether owner, reaches settlement with NYAG	0.543
4/29/2021	SEC statement on stablecoins	1.277
5/14/2021	FTX and Blockfolio add USDC settlement layer	0.477
5/31/2021	Circle raises $440M from Fidelity, Bloomberg's philanthropy arm, others	0.347
10/6/2021	BIS publishes report on stablecoin regulation	-0.112
11/1/2021	U.S. regulators say issuers of 'stablecoins' should be policed like banks	0.212
4/11/2022	SEC requires companies that safeguard crypto-assets to record them as liabilities	-0.293
5/10/2022	Janet Yellen gives statement on financial risks of stablecoins	-0.168
6/30/2022	EU agrees on MiCA regulation	0.294
9/20/2022	Robinhood lists USDC on its platform	0.216
10/14/2022	SEC's Gensler says CFTC authority over stablecoins should be bolstered	-0.546
2/21/2023	Mastercard to allow crypto payments in Web3 via USDC settlements	0.230
4/15/2023	U.S. House publishes stablecoin draft bill	0.065
4/20/2023	EU parliament backs world's first comprehensive rules for cryptoassets	-0.372
5/16/2023	EU Council adopts first legal framework to regulate crypto sector	-0.065
6/21/2023	Fed Chair Powell says central bank needs 'robust' role overseeing stablecoins	-0.025
8/8/2023	Circle launches 'programmable wallets'	0.222
9/29/2023	Circle intervenes in Binance SEC case, argues stablecoins aren't securities	-0.481
10/31/2023	Retail investors can no longer mint USDC directly through Circle	-0.053
11/6/2023	Bank of England, FCA & PRA publish UK's future regulatory regime for stablecoins	-0.167
4/11/2024	Circle enables USDC transfers for BlackRock's first tokenized fund	0.143
4/18/2024	Binance's $1B emergency 'SAFU' fund now makes up 3% of UDSC supply	0.629
5/15/2024	Circle files to shift legal home from Ireland to U.S.	0.442
7/1/2024	Circle is first global stablecoin issuer to comply with MiCA	0.215
11/14/2024	Tether moves into tokenizing stocks and bonds	0.703
12/11/2024	Circle and Binance Enter into a Strategic Partnership	0.491
1/21/2025	Circle acquires Hashnote	1.621
1/23/2025	Trump signs executive order for crypto working group	0.313
2/4/2025	US Senator Hagerty introduces GENIUS stablecoin bill	0.803
3/4/2025	Circle's USDC to be first USD Stablecoin in Japan	0.196
3/13/2025	Senate Banking Committee passes GENIUS Act	0.099
4/4/2025	SEC declares stablecoins are not securities	-0.217
4/22/2025	Circle's new payments network solicits banks for cross-border stablecoin settlement	0.399
5/21/2025	Hong Kong passes stablecoin legislation	0.405
5/23/2025	Circle launches its own cross-border payments network	0.275
6/17/2025	Senate passes GENIUS Act	-0.067

Table A.2: Stablecoin news events

Notes: The market capitalization change is calculated as the daily change in the combined market capitalization of USDC and USDT on event days.

B Methodology

B.1 Event-Study Methodology

This section outlines the methodology to estimate the coefficient of interest in the event-study analysis.

Assuming that the simultaneous equation model in Equations 2–3 are correctly specified and Equations 4–6 hold, we can estimate the coefficient of interest, α, using the covariance matrices of Δy_t and Δm_t on event days and control days.

We denote the covariance matrix of $[\Delta y_t, \Delta m_t]$ for sample $j \in \{S, \tilde{S}\}$ as Ω_j:

$$\Omega_j = \begin{bmatrix} \text{Var}_j(\Delta y_t) & \text{Cov}_j(\Delta y_t, \Delta m_t) \\ \text{Cov}_j(\Delta y_t, \Delta m_t) & \text{Var}_j(\Delta m_t) \end{bmatrix}. \tag{16}$$

The equation above can be expressed analytically in terms of the coefficients and shocks by substituting Δy_t and Δm_t with Equations 2 and 3 and applying definitions of variance and covariance.

The difference in the two covariance matrices can then be expressed as:

$$\Delta\Omega = \Omega_S - \Omega_{\tilde{S}} = \frac{(\sigma_{\nu,S} - \sigma_{\nu,\tilde{S}})}{(1-\alpha\beta)^2} \begin{bmatrix} \alpha^2 & \alpha \\ \alpha & 1 \end{bmatrix}. \tag{17}$$

Using elements of the $\Delta\Omega$ matrix, we can solve for α in a number ways, all of which involving dividing one element of $\Delta\Omega$ with another element. For example,

$$\alpha = \frac{\Delta\Omega_{1,2}}{\Delta\Omega_{2,2}} = \frac{\text{Cov}_S(\Delta y_t, \Delta m_t) - \text{Cov}_{\tilde{S}}(\Delta y_t, \Delta m_t)}{\text{Var}_S(\Delta m_t) - \text{Var}_{\tilde{S}}(\Delta m_t)}. \tag{18}$$

To estimate $\hat{\alpha}$ using the sample of event and control days, we implement an instrumental variables approach from Rigobon and Sack (2004). This involves regressing the outcome variable of interest on $\Delta\mathbf{m} \equiv (\Delta\mathbf{m}'_S, \Delta\mathbf{m}'_{\tilde{S}})'$ using the instrument $\Delta\tilde{\mathbf{m}} \equiv (\Delta\mathbf{m}'_S, -\Delta\mathbf{m}'_{\tilde{S}})'$. The coefficient of this IV regression corresponds to the sample analogue of α.

B.2 SVAR Methodology

This section outlines the assumptions and the key steps to derive the structural impact vector $\mathbf{s}_1$ using heteroskedasticity-based identification.

We formally assume that the movements in the stablecoin market capitalization Δm_t can be attributed to both stablecoin shocks and other shocks:

$$\Delta m_t = \varepsilon_{1,t} + \sum_{i \neq 1} \varepsilon_{i,t} + \xi_t, \tag{19}$$

where $\varepsilon_{i,t}$ for $i \neq 1$ are other shocks affecting Δm_t and ξ_t captures any measurement error, which we assume to be independent and identically distributed with distribution $\mathcal{N}(0, \sigma_\xi^2)$. Here, Δm_t is the aggregated weekly series of the daily market responses. We assume that the variance of the stablecoin shocks is higher on the identified event dates relative to a set of control dates, while the variances of all other shocks are the same on event dates and control dates:

$$\sigma^2_{\varepsilon_1,S} > \sigma^2_{\varepsilon_1,\tilde{S}}, \tag{20}$$

$$\sigma^2_{\varepsilon_i,S} = \sigma^2_{\varepsilon_i,\tilde{S}}, \text{ for } i = 2, \ldots, n, \tag{21}$$

$$\sigma^2_{\xi,S} = \sigma^2_{\xi,\tilde{S}}, \tag{22}$$

where $\sigma^2_{i,j}$ represents the variance of shock i for sample $j \in \{S, \tilde{S}\}$. As previously mentioned, we define our set of control dates $\tilde{S}$ to be all dates that are at least three days away from any event date.

Using the weekly series of market responses for the event dates and control dates, the assumptions imply that the structural impact vector $\mathbf{s}_1$ is the following:

$$\mathbf{s_1} = \frac{\mathbb{E}_S[\Delta m_t \mathbf{u_t}] - \mathbb{E}_{\tilde{S}}[\Delta m_t \mathbf{u_t}]}{\mathbb{E}_S[(\Delta m_t)^2] - \mathbb{E}_{\tilde{S}}[(\Delta m_t)^2]}. \tag{23}$$

The sample analogue of the equation above is the following:

$$\hat{\mathbf{s}}_\mathbf{1} = \frac{\mathbf{U}'\mathbf{\Delta m}_S - \mathbf{U}'\mathbf{\Delta m}_{\tilde{S}}}{\mathbf{\Delta m}'_S\mathbf{\Delta m}_S - \mathbf{\Delta m}'_{\tilde{S}}\mathbf{\Delta m}_{\tilde{S}}}, \tag{24}$$

where $\mathbf{U}$ is a $T \times n$ matrix of the reduced-form residuals from the VAR, and $\mathbf{\Delta m_j}$ corresponds to a $T \times 1$ vector of the market responses for $j \in \{S, \tilde{S}\}$.

B.3 Shock Series

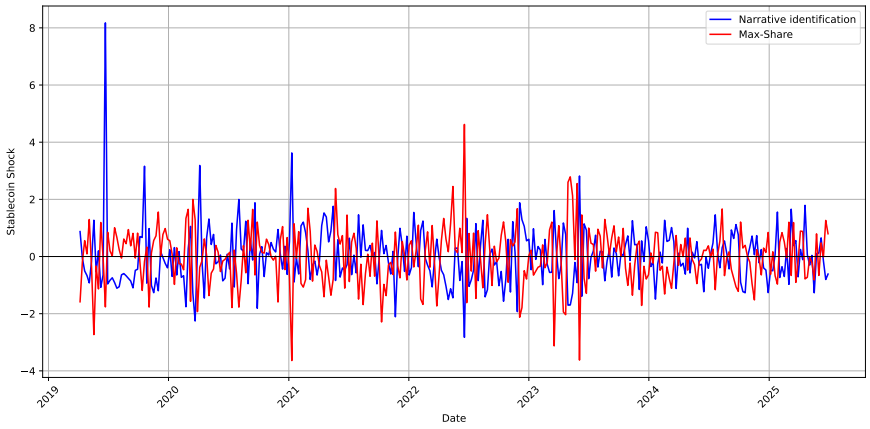


Figure B.1: Weekly shock series from heteroskedasticity-based and max-share approach

Notes: This figure shows the weekly stablecoin shock series from two complementary methods: heteroskedasticity-based identification in a SVAR-IV and the max-share approach.

C Additional Event-Study Results

C.1 Equity Index Responses

	Nasdaq Large Banks (1)	Nasdaq Comm. Banks (2)	Nasdaq Small Banks (3)
Stablecoin Market Cap	0.060	-0.031	-0.028
	(0.116)	(0.120)	(0.120)
Observations	1447	1447	1447

Table C.1: High-frequency responses to stablecoin shocks

Notes: This table reports the results for the event-study analysis using heteroskedasticity-based identification. We use one-day windows for this event-study analysis. All regressions use heteroskedasticity-robust standard errors. *p<0.1; **p<0.05; ***p<0.01.

C.2 Financial Institution Equity Responses

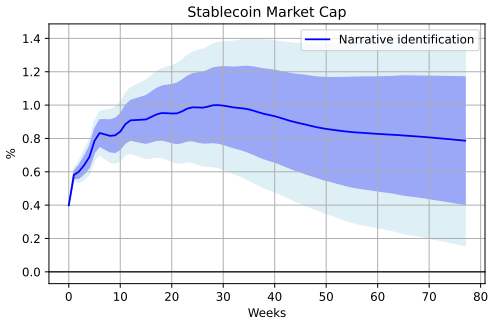
	J.P. Morgan Chase	Bank of America	Wells Fargo	Citi	PNC
	(1)	(2)	(3)	(4)	(5)
Stablecoin Market Cap	-0.010	0.094	0.085	0.041	0.018
	(0.110)	(0.120)	(0.140)	(0.154)	(0.133)
Observations	1404	1447	1404	1226	1226
	U.S. Bank	Trust Financial	M&T Bank	Fifth Third Bank	Huntington
	(6)	(7)	(8)	(9)	(10)
Stablecoin Market Cap	0.039	0.106	-0.057	0.068	0.145
	(0.154)	(0.142)	(0.149)	(0.163)	(0.186)
Observations	1226	1447	1447	1226	1447
	Wintrust	Commerce	United	Hancock	OZK
	(11)	(12)	(13)	(14)	(15)
Stablecoin Market Cap	-0.023	-0.128	-0.046	-0.037	-0.081
	(0.160)	(0.108)	(0.131)	(0.163)	(0.153)
Observations	1502	1502	1502	1502	1502
	First Fin.	International	Texas	Eastern	TFS
	(16)	(17)	(18)	(19)	(20)
Stablecoin Market Cap	0.027	-0.068	0.037	0.206	0.120
	(0.128)	(0.135)	(0.171)	(0.143)	(0.104)
Observations	1502	1502	1502	1082	1502

Table C.2: High-frequency responses to stablecoin shocks

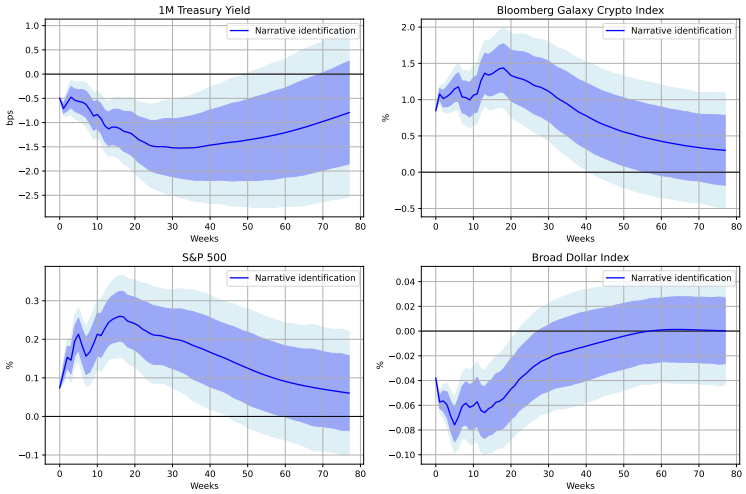
Notes: This table reports the results for the event-study analysis using heteroskedasticity-based identification for the top non-community (columns 1-10) and community banks (columns 11-20) with the highest market capitalization in the U.S. We use one-day windows for this event-study analysis. All regressions use heteroskedasticity-robust standard errors. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

D Additional Impulse Responses

D.1 Alternative Event Selection



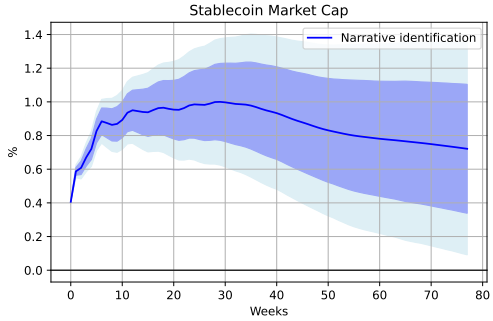
(a) Stablecoin market cap



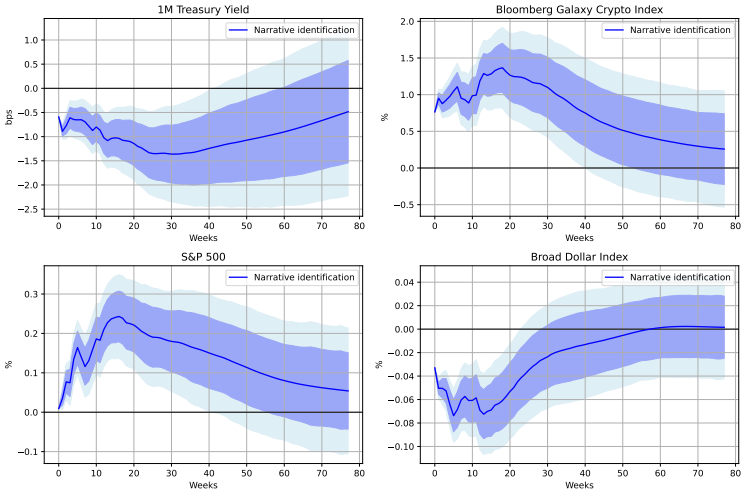
(b) Other outcome variables

Figure D.1: Impulse responses to a stablecoin shock: excluding economic release dates

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.



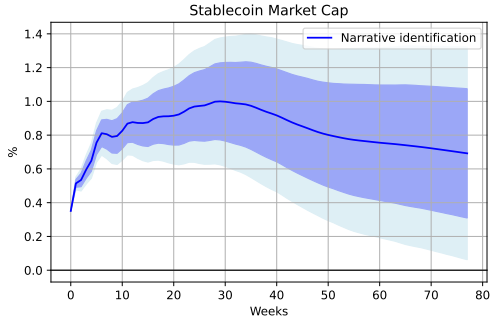
(a) Stablecoin market cap



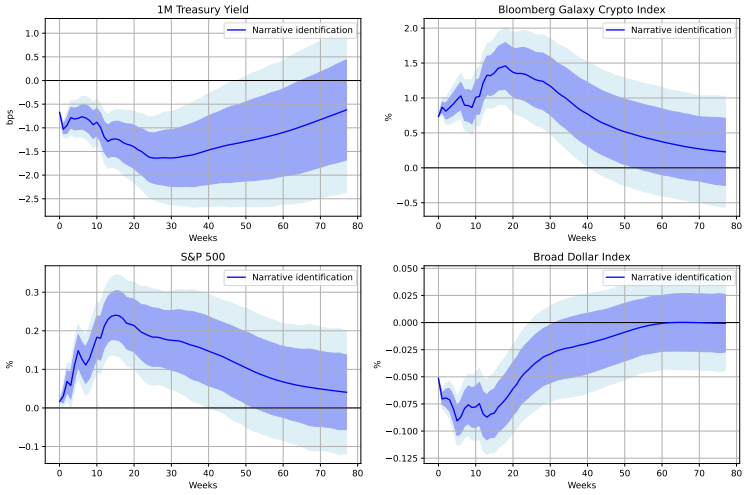
(b) Other outcome variables

Figure D.2: Impulse responses to a stablecoin shock: regulatory events only

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.



(a) Stablecoin market cap



(b) Other outcome variables

Figure D.3: Impulse responses to a stablecoin shock: strongest events only

Notes: This figure shows the impulse responses to a stablecoin shock estimated using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.

D.2 Alternative specifications

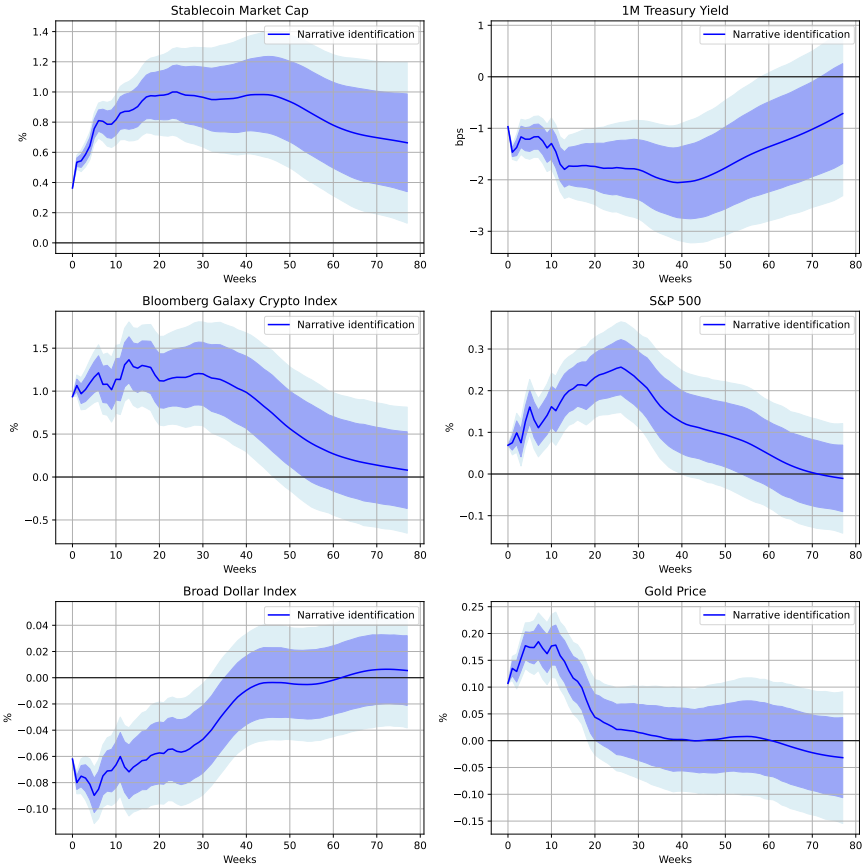


Figure D.4: Impulse responses to a stablecoin shock: adding gold prices

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.

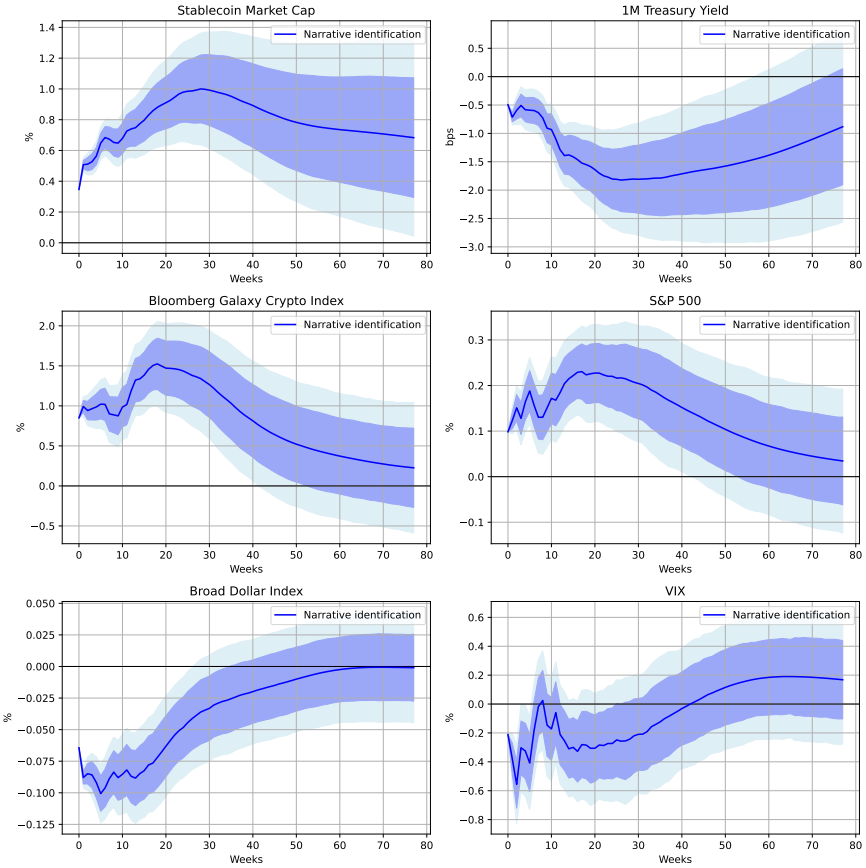
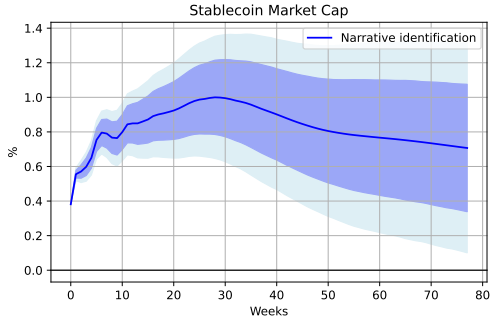
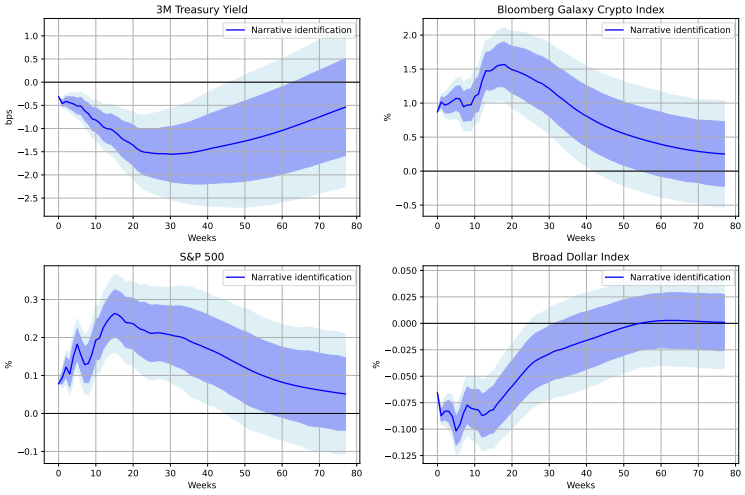


Figure D.5: Impulse responses to a stablecoin shock: adding VIX

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.



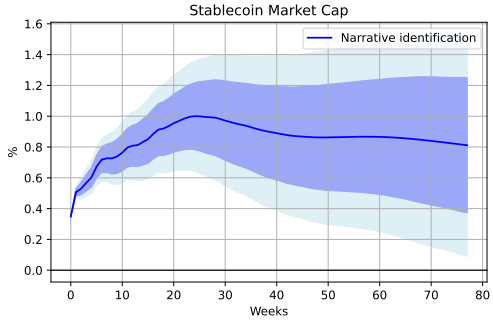
(a) Stablecoin market cap



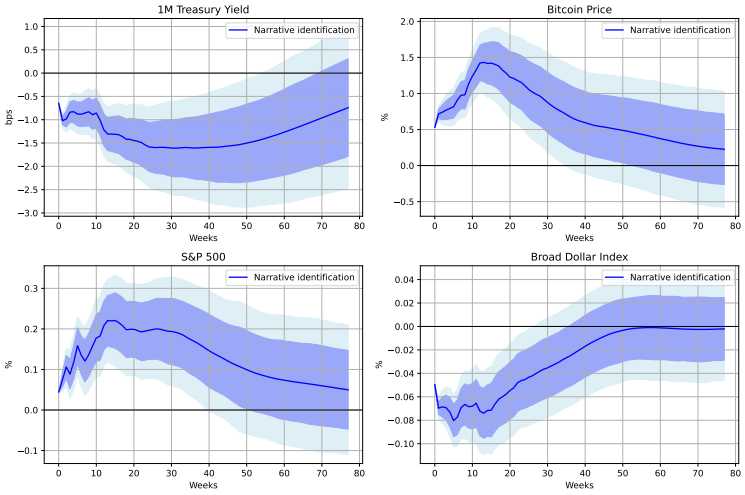
(b) Other outcome variables

Figure D.6: Impulse responses to a stablecoin shock: using 3-month Treasury yields

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.



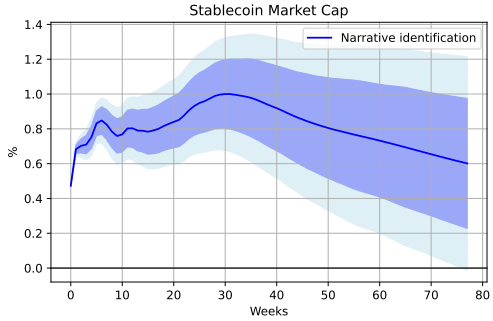
(a) Stablecoin market cap



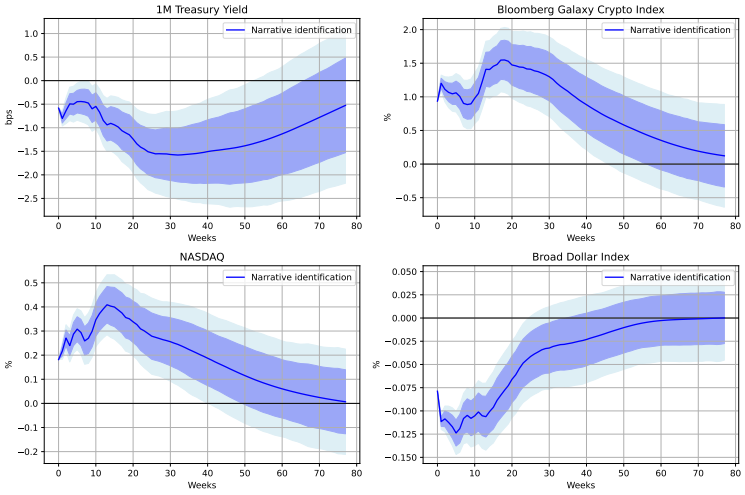
(b) Other outcome variables

Figure D.7: Impulse responses to a stablecoin shock: using Bitcoin price

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.



(a) Stablecoin market cap

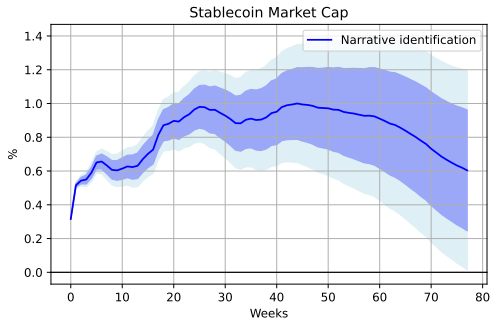


(b) Other outcome variables

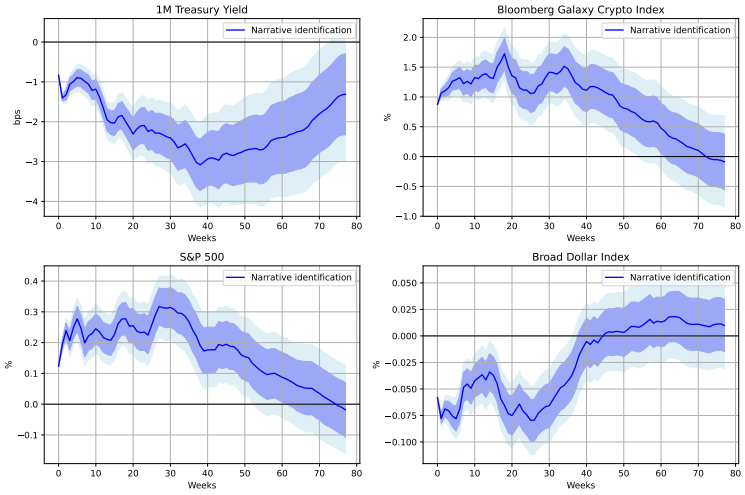
Figure D.8: Impulse responses to a stablecoin shock: using Nasdaq-100

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.

D.3 Varying lag order



(a) Stablecoin market cap

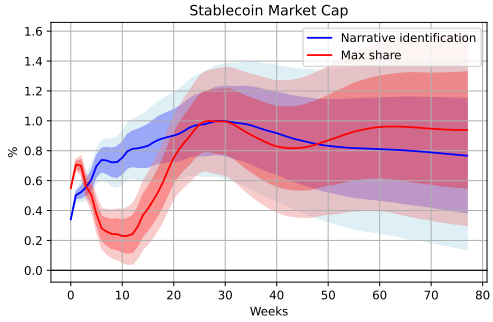


(b) Other outcome variables

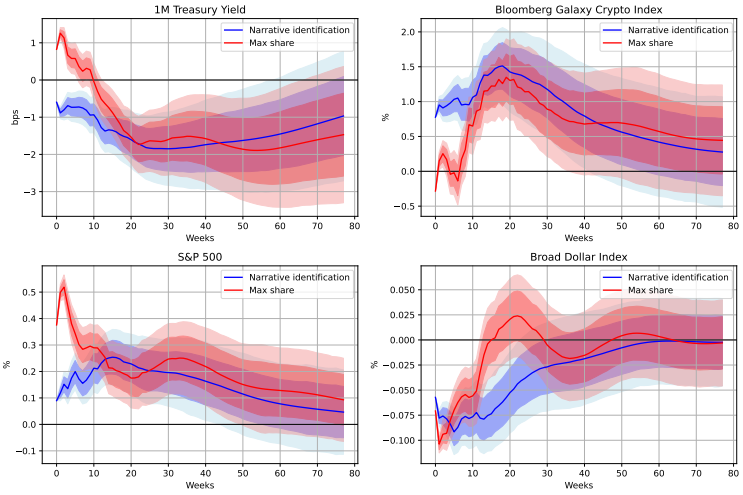
Figure D.9: Impulse responses to a stablecoin shock: 26 lags

Notes: This figure shows the impulse responses to a stablecoin shock using heteroskedasticity-based identification in a SVAR-IV. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.

D.4 Varying horizon length



(a) Stablecoin market cap



(b) Other outcome variables

Figure D.10: Impulse responses to a stablecoin shock: horizon length of 26 weeks

Notes: This figure shows the impulse responses to a stablecoin shock using two complementary methods: heteroskedasticity-based identification in a SVAR-IV and the max-share approach. The shock is scaled such that it corresponds to a 1 percent increase in the stablecoin market capitalization at the peak of responses. The solid lines represent the point estimates; the dark and light shaded areas correspond to the 68 and 90 percent confidence intervals, respectively. We use residual-based moving block bootstrap standard errors from Jentsch and Lunsford (2019) with 10,000 replications.